ILKOM Jurnal Ilmiah Vol. 17, No. 2, August 2025, pp. 131-139
Accredited 2nd by RISTEKBRIN No. 10/C/C3/DT.05.00/2025; E-ISSN 2548-7779 | P-ISSN 2087-1716

YOLOv10 for Real-Time Detection of Personal Protective Equipment on Construction Workers

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Article history: Received March 16, 2025; Revised April 22, 2025; Accepted August 04, 2025; Available online August 14, 2025.

Abstract

This study addresses the challenges of detecting Personal Protective Equipment (PPE) on construction sites, where work-related accidents frequently occur due to the incomplete use of PPE, which can lead to fatal outcomes. The objective of this research is to evaluate the use of the YOLOv10 model a lightweight and efficient object detection architecture to detect various PPE items: safety helmets, safety vests, gloves, and safety boots. The dataset consists of 1,620 images and was split using two configurations: 70:20:10 and 80:10:10 for training, validation, and testing sets, respectively. The YOLOv10 model was evaluated using the key metric of Mean Average Precision (mAP). The evaluation results demonstrate the model's capability to accurately detect PPE, despite variations in data splitting and the number of epochs used. The findings show that the YOLOv10 algorithm performs very well in detecting PPE. On manually processed datasets, the YOLOv10-M model achieved a mAP50 of 97.8% with a 70:20:10 split and 98.4% with an 80:10:10 split. Meanwhile, on datasets processed using Roboflow, the YOLOv10-B model obtained a mAP50 of 85.2% with the 70:20:10 split, and the YOLOv10-S model reached 84.6% on the 80:10:10 split. These findings indicate that YOLOv10 delivers a significant performance improvement in PPE detection compared to previous approaches. The algorithm's ability to achieve high mAP50 scores under certain conditions highlights its potential for real-time implementation in construction environments, where accurate and timely PPE detection is crucial to reducing future workplace accidents.

Keywords: Construction; Personal Protective Equipment; PPE; YOLOv10.

Introduction

Construction sites are inherently hazardous environments due to their dynamic nature. Accidents frequently occur as a result of workers' lack of awareness, training, and experience, as well as non-compliance in wearing Personal Protective Equipment (PPE), insufficient supervision, and equipment malfunction [1], [2]. Health and safety officers are responsible for educating employees about safety protocols and the appropriate selection of workwear. However, challenges arise when employees disregard safety regulations.[3], [4], [5]. Personal Protective Equipment (PPE) is essential for protecting workers from hazards such as tools, extreme temperatures, and mechanical risks. According to guidelines from the Occupational Safety and Health Administration (OSHA), PPE is categorized into five types: Head, Upper Body, Hands, Feet, and Full Body. Its selection must be carried out carefully to minimize the risk of injury and ensure worker safety.[6], [7], [8], [9]

The risk of accidents and injuries on construction sites is extremely high [10], With approximately 2.3 million workers experiencing work-related accidents or illnesses each year, and more than 6,000 fatal accidents occurring every day [11]. Worker safety is a top priority, where the proper use of PPE such as helmets, masks, and vests can prevent injuries and fatalities [12], [13], considering that accidents at industrial sites continue to rise and cause significant losses for both individuals and organizations [14], [15]. Data on occupational accidents across various sectors can be seen in **Table 1** [16], [17].

Table 1. Occupational Accident Data

No	Sector	Total Cases	Percentage
1	Construction	93,748	40%
2	Mining	58,592	25%
3	Manufacturing	46,874	20%
4	Transportation and Agriculture	35,155	15%

Source: Indonesia Safety School (2024)

http://dx.doi.org/10.33096/ilkom.v17i2.2544.131-139

You Only Look Once (YOLO) revolutionized the field of computer vision when it was introduced in 2015 by Joseph Redmon et al. through the paper "You Only Look Once: Unified, Real-Time Object Detection." This paper transformed object detection into a single-step regression problem, directly mapping image pixels to bounding boxes and class probabilities. This unified approach enabled the simultaneous prediction of multiple bounding boxes and class probabilities, significantly improving both speed and accuracy. Since its inception, the YOLO series has continued to evolve, becoming one of the foundational pillars of real-time object detection [18], [19]. YOLOv10 was first introduced by Wang et al. in 2024 and published in the journal titled "YOLOv10: Real-Time End-to-End Object Detection." This latest version pushes the boundaries further with innovative approaches aimed at reducing computational load while maintaining high accuracy. YOLOv10 incorporates advanced techniques such as NMS-free training and holistic model design, making it highly efficient for edge devices with limited computational resources.[20], [21], [22], [23].

AI-based systems, particularly those utilizing YOLO neural networks, offer efficient solutions for real-time detection of PPE usage in the workplace [24]. By leveraging the YOLO object detection algorithm, this technology can recognize various types of PPE such as helmets, safety goggles, vests, shoes, and gloves and verify their correct placement on the worker's body. One of YOLO's key strengths is its ability to process data quickly, making it well-suited for implementation in camera-based monitoring systems without disrupting workers' activities [25], [26]. One of the main challenges in developing such systems is generating a representative dataset. With proper data collection and processing strategies, the dataset can accurately reflect real-world conditions. A well-prepared dataset enables the AI system to operate more efficiently and reliably in ensuring compliance with occupational safety standards. [27].

A study using YOLOv3 and RCNN with image sizes of 416×416 pixels and a dataset of 5,000 helmet images achieved a mAP of 97.12% [28]. Another study employed 608×608 pixel images with a dataset of 1,300 images consisting of six types (person, vest, and helmets in blue, red, white, and yellow), comparing the performance of YOLOv3, YOLOv4, and YOLOv5. The highest mAP was obtained using YOLOv5, which reached 86.55% [29]. YOLOv4 has also been used in previous research to detect human movement in real-time [30]. Another study using image resolution of 640×640 pixels showed promising results in safety object detection. By using the YOLOv5x model on a dataset of 5,000 safety helmet images, a mAP of 92.44% was achieved [31]. A dataset containing 1,699 images for detecting classes such as person, vest, glasses, head, and helmets (red, yellow, blue, and white) using the YOLOx-m model resulted in the highest mAP of 89.84% [32]. In addition, a dataset of 6,045 images for helmet detection using the YOLOv5 method recorded a mAP of 94.7% [33], as shown in **Table 2**.

Table 2. Comparison of Related Work

Model	Object Detection	Description	Reference
YOLOv3 and RCNN	Helmet	Image size: 416×416	[28]
YOLOv3, v4, v5	Person, vest, and helmet (blue, red, white, yellow)	Image size: 608×608	[29]
YOLOv5	Helmet	Image size: 640×640	[31]
YOLOx-m	Person, vest, glass, head, helmet (red, yellow, blue, white)	Rotation: −10° to +10°	[32]
YOLOv5	Safety Helmet	Grayscale images	[33]

Based on the results in **Table 2**, no previous study has implemented YOLOv10 for PPE detection with evaluations involving various image rotation angles to enhance the model’s robustness against perspective variations in the field. This study proposes the use of YOLOv10 with a resolution of 640×640 pixels and testing on PPE items such as yellow safety helmets, safety vests, gloves, and safety boots. The dataset used in this study was augmented with rotation angles of 0°, −45°, 45°, −90°, 90°, and 180° to simulate real-world variations in image capture angles.

Method

Several steps were carried out in this study to detect the use of PPE on construction workers, including data collection, data rotation, non-color augmentation, pre-processing, data splitting, implementation of YOLOv10, and analysis and evaluation to ensure that all workers are wearing PPE correctly and in accordance with established safety standards. The research stages are illustrated in **Figure 1**.

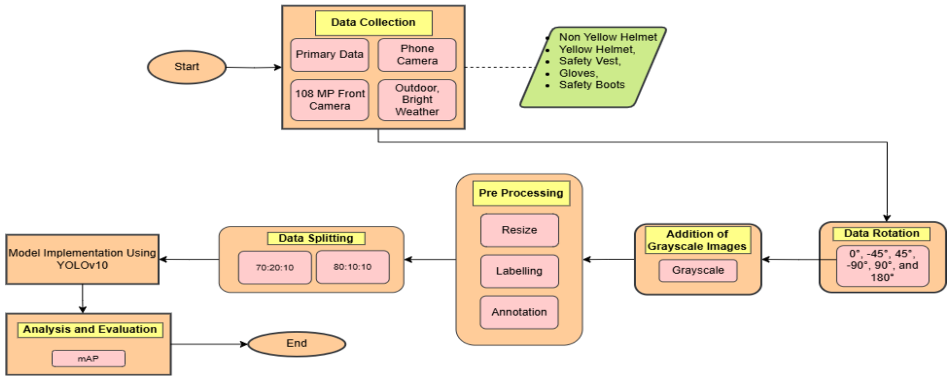

Figure 1. Research Workflow

A. Data Collection

This study utilized primary data collected through frame-by-frame image capture using a Redmi Note 10 Pro smartphone camera with a resolution of 108 MP. The data were gathered in an outdoor setting under natural lighting to achieve optimal results, documenting workers wearing PPE such as helmets, vests, gloves, and safety boots. A total of 135 photos were collected, with sample data shown in **Figure 2**.

B. Data Rotation

This study applied data augmentation by rotating the images in the dataset at angles of 0°, −45°, 45°, −90°, 90°, and 180°. This technique was used to increase the variation in the training data, enabling the YOLOv10 model to be more adaptive in detecting objects with different orientations. The rotation is expected to help the model consistently recognize objects even when their positions or angles change, especially in dynamic construction environments. At this stage, the total number of images increased to 810, as illustrated in **Figure 3**.

Figure 2. Data Collection

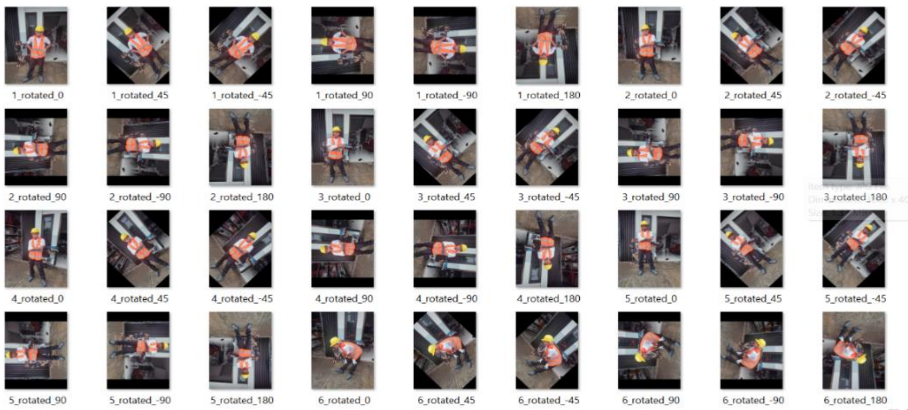

Figure 3. Data Rotation

C. Pre-Processing

To enhance object detection performance, a data augmentation process was carried out, starting with the conversion of images to grayscale format, as shown in **Figure 4**. This step aims to eliminate color information so that the model can focus more on key features such as shape, edges, and object textures, while minimizing the influence of irrelevant color variations. This approach is also expected to improve detection consistency under varying lighting conditions and in dynamic construction environments. This process resulted in 810 grayscale images, which were further augmented through rotation, increasing the total dataset from 135 to 1,620 images. Considering the original image resolution of 3,000 × 4,000 pixels was relatively high and inefficient for processing, all images were resized to 640 × 640 pixels to match the input requirements of YOLOv10 and to reduce computational load without sacrificing important visual information. All pre-processed data were then labeled and annotated into five categories: person, yellow helmet, non-yellow helmet, glove, and boots, as shown in **Figure 5**.

D. Data Splitting

At this stage, the dataset was divided into training, validation, and testing sets using two ratio schemes: 70:20:10 and 80:10:10, from a total of 1,620 images. The selection of these schemes was based on a previous study that used a 64:16:20 split and achieved a mAP of 72.3% [33]. Therefore, experiments using the 70:20:10 and 80:10:10 splits were chosen to evaluate the effect of data proportions on model performance more optimally. The detailed results of the data splitting process are presented in **Table 3**.

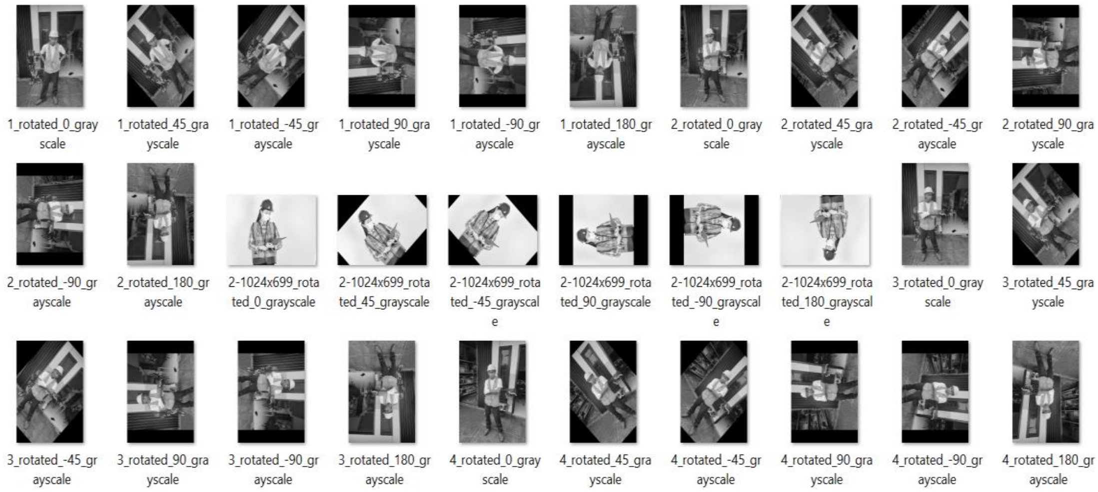

Figure 4. Grayscale Images

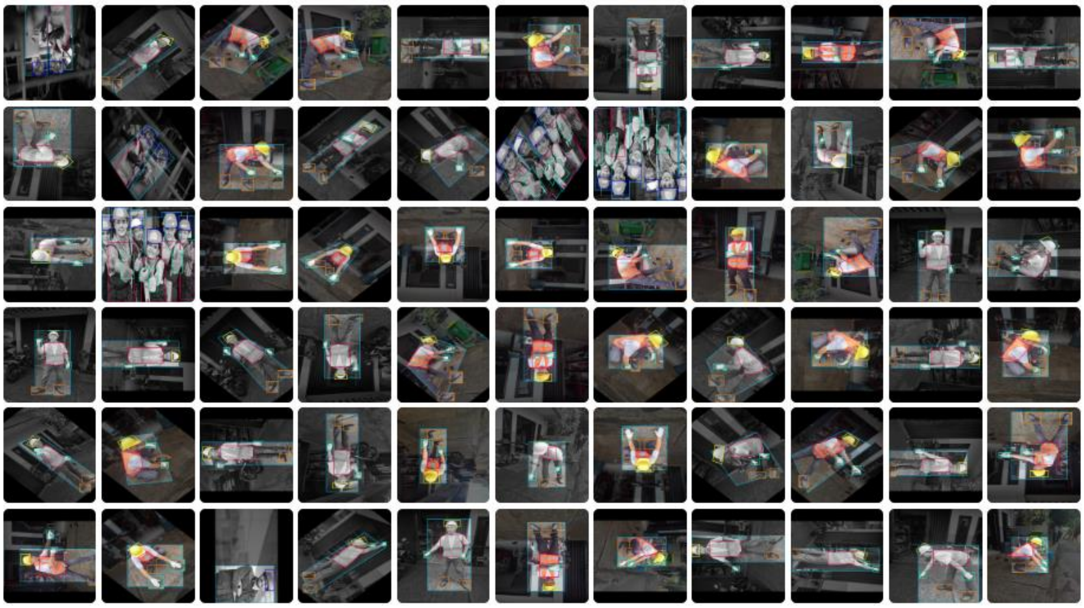

Figure 5. Pre-processing

E. Analysis and Evaluation

The performance of the YOLOv10 model was evaluated using the mAP metric, with a focus on PPE class detection. The model demonstrated high accuracy in detecting various types of PPE, despite variations in data splitting and the number of training epochs. A batch size of 16 was used during training, meaning the model processed 16 images per iteration. The learning rate was set automatically, allowing the system to adjust the learning pace dynamically during training. Optimization was carried out using the AdamW optimizer, which combines the advantages of Adam with weight decay regularization to enhance model performance. Roboflow was utilized to accelerate the processes of annotation, augmentation (such as grayscale and rotation), and automated splitting of the dataset into training, validation, and testing sets. While the manual approach provided full control over data content and distribution, Roboflow offered efficiency and ease of use, especially when managing large-scale datasets. The performance differences between the two approaches were likely due to variations in data splitting methods and label inconsistencies in some images. Nevertheless, the model overall demonstrated excellent performance in accurately detecting PPE.

F. Research Instrument

The experiment was conducted using Google Colab Pro with access to an NVIDIA Tesla P100 or T4 GPU and 25 GB of RAM, ensuring efficient training and evaluation of the YOLOv10 model. This implementation utilized deep learning frameworks and image processing libraries for data preprocessing, both optimized for high-performance computing. The cloud-based infrastructure of Google Colab Pro enabled real-time PPE detection and allowed for faster and longer model training compared to local setups, providing scalability for future experiments and real-time applications.

Results and Discussion

This section presents the experimental results of the YOLOv10 model used for PPE detection. We evaluated the model's performance across different data splitting ratios and numbers of training epochs, and compared the outcomes with previous studies. The performance metric considered in this evaluation is limited to mAP.

Table 3. Splitting Data

	Data Splitting	
	70 : 20 : 10	**80 : 10 : 10**
Training	1.134	1.296
Validation	324	162
Testing	162	162

Table 4. Test Results of Data Splits and Epochs 10–50

Data Splitting	**Epoch**	**mAP 50**											
		Manual (%)						**Roboflow (%)**					
		N	S	M	B	X	L	N	S	M	B	X	L
70:20:10	10	88,5	94,9	94,2	93,3	93,1	92,4	64,4	77,2	73,7	72,5	76,1	76,1
	20	93,6	96,8	96,6	96,7	96	96,6	74	80,5	79,8	78,4	80,5	79,7
	30	95,2	97,4	97,4	96,8	97,4	97,2	78,3	83,2	81,6	82,3	82,6	81,7
	40	96,5	97,1	97,6	97,7	97,6	97,1	80,2	82,9	83,2	83	83,5	82,5
	50	96,7	97,4	97,8	97,4	97,7	97,4	81,3	83,4	83,4	85,2	82,8	82,4
80:10:10	10	91,6	97,3	96,5	95,7	95,3	97,5	64,6	77,4	75,5	72,4	73,7	70,6
	20	95,4	97,3	98,1	98,1	96,6	97,4	73,9	81,5	78,6	79,4	77,2	80,8
	30	97	**98,2**	97,4	**98,4**	**98,3**	97,9	77,8	82,7	81,7	82,1	82,6	82
	40	96,5	97,4	**98,2**	97,3	97,8	97,7	79,2	83,6	82,8	82,2	81,9	82,9
	50	**97,7**	98	97,7	98,2	97,9	**98,2**	81,2	84,6	84,1	83,5	82,8	82,5

A. Model Performance Evaluation

To assess the effectiveness of the YOLOv10 model, several experiments were conducted using two different data splitting ratios 80:10:10 and 70:20:10 for training, validation, and testing and varying the number of epochs from 10 to 50 to evaluate the model's generalization capability across different datasets. **Table 4** presents the comparison between manually split data and data processed using Roboflow, with mAP50 as the evaluation metric. In the 70:20:10 manual data split, the highest performance was achieved by the YOLOv10-M model with 50 epochs, reaching a mAP50 of 97.8%. Meanwhile, testing with the Roboflow-generated dataset produced the best result using the YOLOv10-B model at 50 epochs, reaching a mAP50 of 85.2%. For the 80:10:10 split shown in **Table 4**, the highest mAP was obtained using the YOLOv10-M model with 30 epochs in the manual split, achieving 98.4%. On the other hand, testing with the Roboflow dataset yielded the best result using the YOLOv10-S model at 50 epochs, with a mAP50 of 84.6%.

The difference in results between testing using Roboflow and manual testing is most likely due to variations in dataset construction, particularly in the distribution of training and testing data. In manual testing, several samples had more consistent annotations and a data split that allowed the model to learn from relevant case variations. Meanwhile, in testing conducted via Roboflow, there were indications of inconsistencies in image labels and a dataset split that placed validation samples into the testing set, which may have limited the model's ability to effectively learn certain patterns.

Nevertheless, although the Roboflow-based evaluation yielded mAP50 scores above 80% and the manual testing achieved impressive results exceeding 95%, these findings confirm that the developed model is highly capable of accurately recognizing and detecting PPE. This achievement highlights the strong potential for deploying the model in real-world scenarios, particularly in construction environments where strict monitoring of PPE compliance is essential for occupational safety. With consistently high detection performance, the model can be relied upon as a supportive tool for automation in computer vision–based safety systems.

B. Comparison of Results with Previous Studies

The performance of the YOLO model is compared with previous studies, as shown in **Table 5**. A study using YOLOv3 and CNN with a dataset of 1,500 images achieved a mAP50 of 72.3% [34]. In a subsequent study using the YOLOv5x model with 5,000 images and a resolution of 640 × 640 pixels, the mAP50 reached 92.44% [31]. In contrast, the proposed model using YOLOv10 achieved the highest mAP50 score of 98.4%. This comparison highlights the advantages of using YOLOv10 for comprehensive PPE detection, covering five object classes: Helmet, Vest, Glove, Boots, and Person. Meanwhile, the other two studies only included three object classes, making it more difficult to perform complete detection. YOLOv10 successfully recognized PPE objects with a high mAP, even across different data splits and epoch settings.

C. Result Analysis

The results of this study clearly demonstrate that the YOLOv10 model provides a significant improvement in PPE detection compared to previous research. The ability of the YOLOv10 algorithm to achieve high mAP50 scores under certain conditions reflects its potential for real-time implementation in construction environments. Through accurate and precise PPE detection, this technology is expected to contribute to reducing workplace accidents in the future, thereby creating a safer working environment for construction workers.

In addition, the results of this study show that YOLOv10 remains stable across different data splits without exhibiting signs of overfitting, making it suitable for application in scenarios with diverse data. The model not only outperforms previous YOLO versions but also offers a reliable solution for PPE detection in dynamic construction environments. Future research will focus on expanding the dataset and incorporating additional object classes, so that the model can be applied more broadly not only in the construction sector but also in other industries that require computer vision–based safety detection systems.

Table 5. Comparison Between Studied Methods and the Proposed Method

Author	Object Detection	Method	Results
N. D. Nath, A. H. Behzadan, and S. G. Paal [34]	*Worker, Hat, Vest*	YOLOv3 and CNN	Using a dataset of 1,500 images of workers wearing various PPE, a mAP50 of 72.3% was obtained.
A. Hayat and F. Morgado-Dias [31]	*Head, Helmet, Person*	YOLOv5	Using 5,000 images of safety helmets with a data split of 60% training, 20% testing, and 20% validation at a resolution of 640×640 pixels, the YOLOv5x model achieved a mAP50 of 92.44%.
Proposed Research	*Helmet, Vest, Glove, Boots, Person*	YOLOv10	For the 70:20:10 data split, manual testing showed the highest mAP50 of 97.8% at epoch 50 with the YOLOv10-M model, whereas testing using Roboflow achieved the highest mAP50 of 85.2% at the same epoch with the YOLOv10-B model. In the 80:10:10 data split, manual testing recorded the highest mAP50 of 98.4% at epoch 30 with the YOLOv10-M

Author	Object Detection	Method	Results
			model, while testing with Roboflow yielded the highest mAP50 of 84.6% at epoch 50 using the YOLOv10-S model.

Conclusion

This study demonstrates significant results for the YOLOv10 algorithm in detecting PPE, achieving a mAP50 score of 98.4% with the YOLOv10-M model on the 80:10:10 manually split dataset. Meanwhile, the 70:20:10 manual split yielded a mAP50 score of 97.8% with the YOLOv10-M model. Testing with Roboflow on the 70:20:10 dataset achieved a mAP50 score of 85.2% using the YOLOv10-B model, while the 80:10:10 Roboflow dataset reached a mAP50 of 84.6% with the YOLOv10-S model.

This study has not yet considered PPE detection under extreme lighting conditions or unusual body positions, which may affect the model's performance in real-world scenarios. The study also has limitations regarding the quantity and diversity of the data used, as well as reliance on the quality of manual and automated annotations from Roboflow. Future research should focus on expanding the dataset to include various lighting conditions and worker position variations, along with further optimization of Roboflow-based testing to achieve higher mAP50 scores. These findings have significant implications for PPE detection in construction environments and hold potential for real-time implementation on construction sites.

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Supplementary Material

Supplementary material that may be helpful in the review process should be prepared and provided as a separate electronic file. That file can then be transformed into PDF format and submitted along with the manuscript and graphic files to the appropriate editorial office.